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Assessing the economics of processed natural resources - the case of seaweed

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Abstract

The bioeconomy utilizes living organisms and processes them to produce of food, fuel, fine chemicals, and other substances. Macroalgae are promising feedstocks for chemical products while sequestering carbon. There is a need for methodologies for economic and policy analysis of novel bioeconomy technologies, taking into account environmental side effects and physical and economic uncertainties.

The aims of the feasibility study BARD Project No. US-4986-17 F were twofold: First, to develop a methodology to assess the economic feasibility of biological feedstock cultivation and processing into co-products. The methodology addressed various parameters, associated with the new technology, and assessed the performance of the integrated supply chain that includes feedstock and processing to produce sugars and proteins. Second, to apply this system to assess the profitability of producing commodity biochemicals from macroalgae under various assumptions about growth rates of the feedstock, prices and costs, conversion factors in the biorefinery and technological learning.

Following the original objectives of this study, we developed a novel methodology to assess the performance of the integrated two-stage supply chain – feedstock farming and processing into multiple outputs. The modeling framework clarifies that learning in multi-stage supply chain creates a positive externality of co-outputs. Moreover, if learning rate is faster than cost increase, then output grows faster than prices. Next, we demonstrated the application of this non-linear dynamic model on macroalgae (seaweed) farming and processing in the biorefinery into crude proteins and polysaccharide (carrageenan). Our computational experiments identified the set of conditions in terms of costs, prices of outputs, shares of co-outputs in the biorefinery, as well as technological efficiency and R&D efforts that make production of biochemicals from macroalage worthwhile. The results indicate that for average prices of proteins and carrageenan, and for average costs of investment in cultivation farm and the biorefinery, macro algae utilization is cost- efficient. However, profitability of this supply chain is fragile due to high volatility of outputs' prices, as well as wide range of feedstock growth rate and chemical composition. We found that the main constrain for commercialization, is the first stage of the supply chain, namely macroalgae marine cultivation.

The follow up study is planned to investigate the hypothesis that macroalgae derived commodity biochemical could provide a novel, sustainable and economic supply chain for the low- carbon food industry. The big scale macroalgae cultivation involves direct and external effects on marine environment, carbon absorption, potable water, land use and employment. Further analysis on macroalgae external costs and benefits, as well as social welfare analysis, is required for an accurate policy intervention. Accordingly, we will identify policy parameters, including pricing of greenhouse gas sequestration and other externalities, as well as additional policy interventions that may affect the performance of the system.

Summary Sheet

Publication Summary

PubType	IS only	Joint	US only
Review Article	0	0	1
Submitted	0	2	0

Training Summary

Trainee Type	Last Name	First Name	Institution	Country
M.Sc. Student	Voldman	Liran	Yezreel Valley College	Israel
M.Sc. Student	Gladkov	Alexander	Tel Aviv University	Israel
Postdoctoral Fellow	Prabhu	Meghanat	Tel Aviv University	Israel
Ph.D. Student	Robin	Arthur	Tel Aviv University	Israel
Ph.D. Student	Gordon	Benjamin	University of California Berkeley	USA
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Contribution of the collaboration

Israel and the US have been leaders in utilization of algae. Development of the bioeconomy is a major challenge for both countries. The contribution of this research is by providing an assessment tool for evaluation of the economic potential of novel technologies.

The project was a multidisciplinary effort. The economic component designed a model to assess the performance of the supply chain under uncertainty. To address the challenges of macroalgae-based bioeconomy, this research developed the generic modeling of a two-stage production process with a dynamic optimal control approach. We view the design of a supply chain as a constrained optimization problem.

The process-engineering component identified the parameters of production of macroalgae based on the literature and lab experiments. The result of the experiment were integrated to the modeling framework to conduct simulations used to determine the performance parameters (e. g. profitability of a production unit that includes feedstock and processing) that can make macroalgae cultivation and processing biochemical commodities economically viable.

The key feature of the project was the interdisciplinary collaboration. The economic model identified key parameters that were needed for the assessment, and the bioengineering team provided them. The bioengineers helped to modify the economic model and made it more realistic. This collaboration between economists and bio-engineers facilitated the assessment of the integrated supply chain based on cultivation and harvesting technologies, and conversion processes to sugars and proteins. Ultimately, we determine the conditions that make it worthwhile to invest in a new bio-refinery.

Achievements

The bioeconomy has evolved over time to include multiple products and supply chains. The traditional bioeconomy produced grains and fermented them into wine. The modern bioeconomy employs advanced biotechnologies to produce high value chemicals from agriculture and natural resources. This study investigated the economic opportunities and challenges of the bioeconomy focusing on macroalgae utilization. The interest in macroalgae is driven by the fact that being cultivated off-shore, they do not compete for arable land and potable water. In addition, recent developments in the bio-refinery process show the potential to produce not only food and coloring, but also sugars for biofuels, proteins, and high value chemicals.

The contributions of this research are manifold. First, we propose a two-stage dynamic optimal control model for the design and management of a multi-staged supply chain. The model is applied to micro-level decision making, taking into account key supply chain components. The two stages include cultivation of feedstock and then processing it in the biorefinery with possibility for multiple co-production. The study incorporates non-linear profitability impacts of feedstock growth rates, and yields of biorefinery, represented through Learning by Doing (LBD) elasticities. To the best of our knowledge, this study offers a unique modeling approach that explicitly takes into account non-linear stage-specific production costs, and introduces the learning effect. Second, the novelty of our work is in proposing a model with a multi-output profile of the second stage and deriving the conditions for a profitable production bundle. Finally, a series of simulations with parameters based on laboratory experiments is presented to validate the effectiveness of the model and the theoretical insights. More importantly, the analysis allows answering the key policy questions of supporting novel technologies that involve multi-stage co-production process. The importance of the research is in emphasizing the three key pillars in the supply chain based on the novel technology: the initial (fixed) costs, output prices and learning.

The experimental part of the work included the sequential extraction of six products including starch, mineral salts, pigment, ulvan, protein and cellulose, from same initial starting biomass of Ulva sp. by using various extraction procedures in an integrated biorefinery approach. Up to date, we manage to fractionate and recover 77.67±5.33% of the starting biomass, which significantly higher than currently 8-14% product recovery yields in hydrocolloid industry. We recovered 3.52±1.58% of starch, 44.54±0.32 salt, 3.18±1.19% pigment, 8.07±4.18% ulvan, 11.18±3.42% protein, 7.18±0.17% cellulose. The percentage is from the starting dry weight of the biomass.

The theoretical and simulation results highlight the importance of the early period learning, when the entrepreneur absorbs losses for the sake of future profits. In addition, for every rate of learning, the study demonstrates the time to maturity of the technology that declines with the increase in output prices, output of the co-product, and learning rates, but increases with the raise of first unit costs. The simulations reveal that cultivation costs have higher impact on profitability than processing in the biorefinery even if the processing allows for several outputs. Thus, the R&D effort should primarily address the cultivation stage in order to reduce the fixed costs of natural resource utilization. Gaining knowledge and experience in best off-shore cultivation practices is the key to boosting the mass utilization of the renewable resource – macroalgae. Moreover, the simulations indicate that production costs can be sensitive to the learning effort. The first unit (fixed) cost of cultivation of $/ton 4000 appears to be the threshold where LBD can reverse non-profitable production.

This feasibility study should be extended in several directions: The assessment of the integrated choice at the micro-level combining both cultivation and refining parameters while explicitly representing the uncertainty within these processes, is of high importance. Uncertainties and random factors that need to be taken into account are: the demand for final products, the cost of the refining technology, the cost of feedstock production in-house, or the reliability and performance of various external suppliers (Zilberman, Lu and Reardon 2017). According to Reardon and Zilberman (2017), entrepreneurs may invest in protective measures to increase resilience of their supply chains to extreme weather risks. They may geographically diversify their external sources of feedstock to reduce exposure to weather shocks. Therefore, incorporating risk considerations may actually increase the cost of investment in implementing a new innovation, especially if the enterprise is constrained by credit. Moreover, introducing and perfecting new innovations is a random process, and the economic conditions that face a technology also vary over time. Learning takes time, and the dynamics of knowledge accumulation affect the timing of introduction of new innovations, their refinement, and their commercialization. Timing can also affect the decision regarding both the capacity of a new innovation and the extent of reliance on external sources. Here, the dynamic setting using the Real option approach may provide insights on the benefits and costs of delay of investment, as well as on alternative production/cultivation methods or types of feedstocks. Allowing for volatile prices dynamics, will enforce investigating the tradeoff between researching effort and price variability. For example, taking into account price volatility, the entrepreneur might introduce the product in the period when the price is high. Then, the question is, what learning effort will allow the entrepreneur to operate, even if the price declines later on.

Another conceivably important aspect that was out of the scope of this study, is the innovation spillover. As proteins and sugars are produced simultaneously from a given quantity of the seaweed, the accumulation of R&D and experience in processing seaweeds into proteins, can stimulate the efficiency in production of sugars, and vice versa. Therefore, the possibility of correlation between learning rates of co-outputs of the biorefinery should be investigated.

Finally, the present study evaluated the profitability of natural resource utilization without considering the environmental and social externalities. The big scale macroalgae cultivation involves direct and external effects on marine environment, carbon absorption, potable water, land use and employment. If macroalgae-based products, e.g. biofuels, proteins and sugars, crowd-out the use of substitutes, the negative effects of fossil and crop-based energy might be mediated (Zilberman, Rajagopal and Kaplan 2017). Further analysis on macroalgae external costs and benefits, as well as social welfare analysis, is required for an accurate policy intervention. The analysis on the technological prospects of macroalgae biorefinery should evaluate the social net benefit too. The main hypothesis to be evaluated is that macroalgae derived commodity biochemical could provide a novel, sustainable and economic supply chain for the low-carbon food industry.

Changes to Original Research Plan

No major changes were made

Publications for Project US-4986-17 F

Status	Type	Authors	Title	Journal	Vol:pg Year	Coun
Published	Review Article	*David Zilberman, Ben Gordon, Gal Hochman, and Justus Wesseler*	Economics of Sustainable Development and the Bioeconomy	***Applied Economic Perspectives and Policy***	40 : 22-37 2018	US only
Submitted	Other	*Ruslana Rachel Palatnik, Michael Freer, David Zilberman, Alexander Golberg, Mark Levin*	Time to dare and endure: case study of macroalgae two-stage supply Chain with Co-products		: 2018	Joint
Submitted	Other	*Ruslana Rachel Palatnik, Michael Freer, David Zilberman, Alexander Golberg, Mark Levin*	No challenge is too great: case study of macroalgae two-stage supply chain with co-products		: 2018	Joint

Assessing the Economics of Processed Natural Resources - The Case of Seaweed

David Zilberman, Ruslana Rachel Palatnik, Alexander Golberg

BARD Project No. US-4986-17 F

Appendix

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Annex 1*:* **Results of the process-engineering component**

Demonstration of Ulva sp. biorefinery involving combined production starch, salts, lipids, ulvan, protein and cellulose

The original aim was to identify the parameters of production of macroalgae based on the literature and site experiments. The result of the experiment were integrated to the modeling framework to conduct simulations used to determine the performance parameters.

Sustainable economic development depends on sustainable supply of resources for industrial production. Most of the energy and material demand in today's world come from fossil fuel refinery[1]. Biorefineries are the manufacturing units of bio-economies where in one or several biomass feedstocks are processed into a wide range of marketable products including biofuel, food, and biomaterials through jointly applied conversion technologies [1,2].

Marine green macroalgae, also known as seaweeds, are looked upon as promising alternative biorefinery feedstocks for marine biorefinry. This is possible due to its unique chemical composition that contributes towards the harvesting of wide range of potential products with different applications. Green macroalgae have very low or no lignin content, making them attractive feedstock globally for production of bioenergy in recent times. In addition, several advantages are associated with the cultivation of green macroalgae over terrestrial crops such as higher biomass yield, non-requirement of freshwater and arable land[3]. These advantages make them attractive feedstock for biorefinery to supply sustainable food, fuel, and chemical[4,5]. Such sustainable utilization of marine biomass, can thereby strengthen the future maritime economies and low carbon societies [6, 7].

Co-production of two or more products from green macroalgae in an integrated, cascading, biorefinery approach has been followed, thus maximizing the benefits of seaweeds biomass [8–11]. Recently Gajaria et al. [12] reported the extraction of five different chemical products, mineral salts, lipids, ulvan, protein, and cellulose, from U. lactuca. Recently in our laboratory we found a significant amount (21.5%) of starch in Ulva. sp. which was further successfully extracted and characterized[7]. However, to date no study has demonstrated an integrated biorefinery approach to recover marine macroalgal starch together with the other established counterparts.

The goal of this study was to integrate the starch in marine biorefinery process. To achieve this, we investigated the sequential extraction of six products including starch, mineral salts, pigment, ulvan, protein and cellulose, from same initial starting biomass of Ulva sp. by using various extraction procedures in an integrated biorefinery approach. An integrated process was developed in such a way that most of the valuable macromolecules are successively extracted together with the starch extraction. Our work suggests a new marine biorefinery design for extraction of maximum number of value added products. Such efficient and sustainable use of biomass resources, which is of paramount importance, will form the foundation of a future biobased economy.

Method

Fresh Ulva sp. biomass was collected from cultivation facility situated at Israel Oceanographic and Limnological Research (IOLR), Hiafa. It was characterized for initial characteristics as shown in table 1. The fresh biomass (200 g) was mixed 2L of distilled water and homogenized to fine paste. Following scheme, as shown in figure 1, was followed to harvest different products in sequential manner.

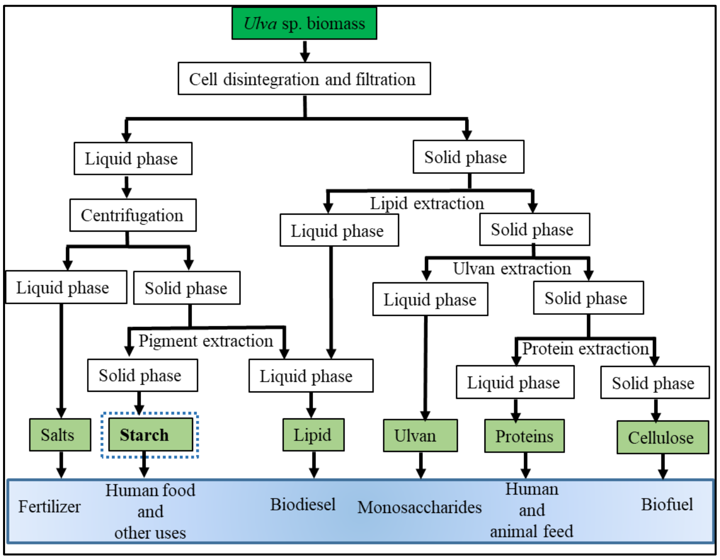

Fig. 1. Green macroalgae (Ulva sp.) biorefinery process for co-production of a wide range of products

Results

Characterization of Ulva sp. biomass

Table 1: Characteristics of Ulva sp. biomass (non-washed, and dried at 40 °C) used for biorefinery (Sample from Haifa)

Parameters	**%**
Dry mass (at 40 °C)	30.30
Moisture	10.70
Ash content	34.86
Starch content (% DM)	6.69

Biorefinery products

Salt rich fraction: From the literature it is known that this fraction constitute several types of bioactives including phytohormones and macro- and micro-elements of importance for plant growth and development. Thus, this can be used as nutrient supplement in fertilizing plants.

Previous studies have reported its use as fertilizers on various agronomically important crops thus improving improving yield as well as nutritional quality with reduction in recommended dose of chemical fertilizers. In this study, 44.54±0.32% of DM salt rich fraction was obtained.

Starch rich fraction: Starch in Ulva sp. is stored in granular form of 5-7 μm size. This starch can be utilized in various industries and are used for multiple applications including food, fermentation, textile, cosmetics, pharmaceutical, packaging, synthetic polymer industries and in biotechnological applications13. It can further be used for generation of by converting it to biofuel using fermentation. In this study, 3.52±1.58% of DM starch rich fraction was obtained.

Lipid rich fraction: Lipids and their respective fatty acids; saturated fatty acids (SFA) without double bonds in acyl chain, monounsaturated fatty acids (MUFA) with one double bond in acyl chain and polyunsaturated fatty acids (PUFA) with two or up to 6 double bonds in acyl chain are one of the crucial fundamental molecules for human nutrition. Seaweeds have relatively low lipid contents, but the composition rich in C18 (linoleic and alpha-linolenic) fatty acids and low in C20 PUFAs; a combination that has been associated with the prevention of cardiovascular diseases, osteoarthritis and diabetes. In this study, 3.18±1.19 % of DM lipid rich fraction was obtained.

Ulvan rich fraction: Ulvan is the major water soluble sulfated polysaccharide (SPs) found in Ulva sp. Several potential applications have been investigated for such SPs: animal feed, antioxidant, antitumor, anticoagulant, immune modulator, and biomedical applications such as drug delivery and tissue engineering 14–16. In this study, 8.07±4.18 % of DM ulvan rich fraction was obtained.

Protein rich fraction: Proteins are importance in terms of both commercially valued product and as a forever demanded nutritional supplement. The protein content of macroalgae is known to contain all essential amino acids (EAA) although seasonal variations in their concentrations are reported in the literature. In this study, 11.18±3.42% of DM protien rich fraction was obtained.

Cellulose rich fraction: The cellulose extraction was the final step in this integrated approach as it is found to be least affected by the up-stream treatments compared to any other components of the procedure . After ulvan, cellulose is the major polysaccharide found in marine green macroalgae which has potential applications today for paper industries and as a feed stock of the rapidly emerging era of biofuels. Besides these two potential industrial applications, cellulose has been a preferred polymer for synthesis of nanocomposites, microcrystals and nanocrystals. In this study, 7.18±0.17% of DM protien rich fraction was obtained.

Table 2: Yield of each fraction from Ulva sp biomass during sequential extraction.

	Fractions	**(% of original DM)**
1	Starch rich fraction	3.52±1.58
2	Salt Rich fraction	44.54±0.32
3	Pigment rich fraction	3.18±1.19
4	Ulvan Rich fraction	8.07±4.18
5	Protein rich fraction	11.18±3.42
6	Cellulose rich fraction	7.18±0.17
	Total	77.67±5.33

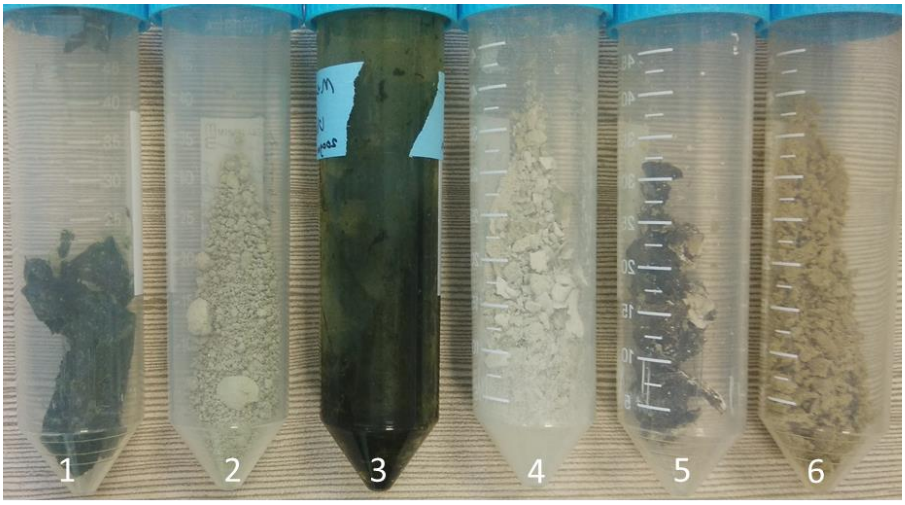

Fig. 2. Shows different fractions (1 to 6) obtained in biorefinery.

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Annex 2: Time to dare and endure: case study of macroalgae two-stage supply Chain with Co-products

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Abstract

The bioeconomy utilizes living organisms and processes them to produce food, fuel, fine chemicals, and other substances. The aims of the study are twofold: First, we develop a novel methodology to assess the performance of the integrated supply chain that includes key components - macroalgae biomass production, and, its processing in the biorefinery. The methodology addresses various uncertainties associated with the new technology through learning by doing parameters, and evaluates the economic feasibility of producing sugars and proteins from biomass. Second, we demonstrate the accuracy of the methodological framework using macroalgae based biorefinery as a testing ground to visualize and validate the modeling results. Our computational experiments reveal insights about the profitability conditions of producing commodity biochemicals from macroalgae under various assumptions about outputs prices' growth rates, cost factors and elasticities of learning by doing of various production stages. The research answers the key policy questions in R&D investment, namely, what production stage should be primarily addressed for cost-effective R&D effort? The results indicate that high marine cultivation costs are currently the main obstacle for profitable macroalgae utilization.

Keywords: *dynamic optimal control, two stage production, learning by doing, biorefinery, macroalgae*

1. Introduction

The bioeconomy provides a possible solution for the demand to natural resources by substitution of the unrenewable resources with resources derived from biomass (Enriquez 1998). The bioeconomy consists of complex supply chains that include biomass production, transportation, conversion into products at biorefineries, and distribution. One of the major challenges is developing economic decision-making tools to assess novel biotechnologies that incorporate the complex multi-level systems including environmental implications and uncertainties about feedstock production, refining technologies, markets, and policies.

Macroalgae (seaweed) are promising feedstocks for energy and chemical products while sequestering carbon (Palatnik and Zilberman, 2017). An expanding body of evidence has demonstrated that marine macroalgae can provide a sustainable alternative source of biomass for food, feeds, fuel and chemicals generation (Bruhn, et al., 2011)(Bruhn et al. 2011; Wargacki et al. 2012; van der Wal et al. 2013).

Macroalgae, which contain very little lignin and do not compete with food crops for arable land or potable water, have stimulated renewed interest as additional candidates for future sustainable food, platform chemicals and fuel (biofuel) feedstocks. Macroalgae have been harvested throughout the world as a food source and as a commodity for the production of hydrocolloids for centuries. However, to date macroalgae still account for only a tiny percent of the global biomass supply with $\sim 17 \cdot 10^6$ fresh weight (FW) ton of macroalgae in comparison to $16 \cdot 10^{11}$ tons of terrestrial crops, grasses and forests (Pimentel and Pimentel, 2008; Roesijadi et al. 2010; Pimentel 2012). Concerns over net energy balance, potable water use, environmental hazards, and processing technologies call into question the potential for terrestrial biomass such as cereals crops and lignocellulose biomass to provide efficient sustainable answers to future food and energy challenges (Gerbens-Leenes et al. 2009). Cost-effective cultivation and dehydration difficulties currently limit the scale of microalgae technologies implementation (Hannon et al. 2010). At the same time, an expanding body of evidence has demonstrated that marine macroalgae can provide a sustainable alternative source of biomass for food, feeds, fuel and chemicals generation (Bruhn et al. 2011; Wargacki et al. 2012; Kraan 2013; van der Wal et al. 2013; Aitken et al. 2014).

The vast literature on the bioeconomy recognizes that the system includes at least two components: feedstock cultivation and refining. Rajagopal et al. (2009) conducted a survey that describes both the components of advanced biofuel systems and the considerations of economic and social impacts. Another strand of literature assesses the economics of corn and sugarcane based ethanol and biodiesel (Babcock et al., 2011; Crago and Khanna 2014; Jain et al., 2010). Much of the literature emphasizes the economics of the feedstock while recognizing the importance of integration of feedstock cultivation and processing. However, there are not many frameworks that assess the integrated choice at the micro-level combining both cultivation and refining parameters while taking into account uncertainty of these processes.

This is unlike other renewable technologies, in particular solar energy and electric vehicles, where much emphasis was placed on assessing under what conditions and when these alternative technologies would be profitable using the real option approach (Torani et al., 2016; Lemoine, 2010). This approach allows the introduction of key uncertainties in the system, but must be modified to specific conditions of the problem. This study develops an integrated decision making framework to assess new bioeconomy solutions that incorporate the key stages of the supply chain and apply it to macroalgae.

To address the problem of macroalgae biorefinery economics, this paper develops the generic modeling of two- stage production process with a dynamic programming approach. The detailed assessment of the integrated supply chain that includes cultivation and harvesting technologies, conversion processes to fuels and high value products is performed. The study incorporates for multiple sources of uncertainty such as technology costs, prices of potential outputs, feedstock growth rates, and yields of biorefinery. Analytic results are derived regarding the threshold conditions for profitability of alternative technologies.

The paper focuses on specific macro algae cultivation and bio-refinery. Given the high production costs of macroalgae marin aquaculture and biorefinery, and the uncertainty in profits, the study aims to answer the key policy question: Where the R&D has the most significant impact on the profitability of the novel technology? In other words, where the limited budget of government support should be most efficiently used – in supporting marine aquaculture or in the bio-refinery.

Evidently, the rate of macroalgae growth and the conversion factors – two key parameters in productivity- show a wide range of values, and may be subject to even higher variation due to climatic changes. This variability in yields might have a major effect on cost effectiveness of the technology. Here, the study aims to identify how and under which conditions the new generation of biorefineiries that facilitate macroalgae processing, can enter markets of food, chemicals and fuels. We will investigate the trade-off between technological development and uncertain changes in prices of outputs.

Palatnik and Zilberman (2017) report that even though the literature on economic analysis of macroalgae utilization is rapidely increasing, yet it lacks an established cost function. Most of the studies employ a linear approximation for NREL costs module for corn-stove biorefinery. Our study contributes to the literature bydeveloping an optimal control model with a non-linear approximation to production costs of macro-algae utilization.

The paper continues as follow: section 2 reviews the literature on multi-stage production and the learning by-doing methodology. Section 3 describes the developed model. Section 4 provides the parameters for the simulations. Section 5 presents the simulation results. Section 6 concludes.

2. Literature review

For the analytical methodology to accurately replicate the production process of newly developed bioeconomic technologies, it should incorporate the two key features of the production process: 1. Farming of the feedstock (e. g. corn for ethanol, seaweed - Kappaphycus for Carrageenan production); 2. Biorefining of the feedstock into final (or intermediate) commodities. The next sub-section reviews the economic literature that addressed the two-stage biomass supply-chain optimization.

2.1. Two- stage supply chain

The two-stage supply-chain literature focuses mainly on the following major challenges: inventory optimization, location planning, and feedstock uncertainty.

The significant branch of the two- stage production models are essentially inventory optimization models, where the decision about the optimal inventory of feedstock size or quality affects the second stage of production. For example, Wu and Wang (2015) study the inventory model where in Stage 1 the raw materials are produced into semi-finished items by machines. The production system produces non-conforming quality semi-finished items in out-of-control state. In this system, the rework time of rework items in a two-stage imperfect production system are explicitly considered. Enders et al. (2014) model a single-item inventory system with a high priority lost sales customer class and a lower priority backordering class. They propose a critical level policy and develop a procedure to determine the average performance of a given critical level policy. Isotupa (2015) analyzes a lost-sales inventory system with two classes, and shows that there is a sub-optimal policy under certain conditions. Xu et al., (2017) employ the dynamic programing approach to investigate the inventory rationing problem in a two-product tandem make-to-stock production/inventory system. The authors develop the setting where the management has to decide whether to run or stop production and whether the various classes of demand for both products—intermediate product and finished product - have to be satisfied from available inventory or not—in which case demand is lost—in order to maximize the firm's expected profit.

Another branch of literature provides supply chain analysis for cost minimizing decision upon biorefinery location given the biomass supplier allocation and production site location (e.g. Zamboni et al., 2009; You et al., 2012; Xie and Ouyang, 2013; Roni et al. (2014); Memisoglu and Uster (2015); Marufuzzaman et al., 2016).

These studies are extended by Cundiff et al. (1997), Kim et al., 2011, Chen and Fan (2012), Gebreslassie et al. (2012), Awudu and Zhang (2013), and Marufuzzaman et al. (2014b) to consider system uncertainties (e.g., biomass supply, demand, technology, pricing) in the network design process.

Wu et al., (2015), Quddus et al., (2018) and Wang et al., (2012) are three selected representatives of another stream of research that models the multi-stage production with uncertainty that reflects the renewable energy volatility in power generation. Those studies specify in details the characteristics of renewables such as wind, solar and municipal solid waste (MSW) in the power supply. Here, the second stage output – electricity – is a homogeneous good, whereas our analysis attempts to provide an additional decision parameter that affects the profitability – the output mix might be constructed of two (or more) goods that vary with both costs of production and output prices. Osmani and Zhang (2013) do present the two stage supply chain analysis of bioethanol, but their multi-feedstock decision is made at the first stage.

The recent comprehensive review of optimization-oriented biomass supply-chain designs shows numerous prior works that addressed various important conditions for profitable supply chain (Ghaderi, Pishvaee, & Moini, 2016). This review of 146 studies concludes that researchers have been mostly orientated towards single-feedstock, single-product, single-period, single-objective, and deterministic models without considering all the dimensions of sustainability. The present study contributes to the literature by modeling two important characteristics of natural resource utilization: the ability for multi-output production at the biorefinery; and, accounting for learning effect, i. e. the fact that mass production and production over-time reduces the unit production costs. The next sub-section describes the importance of learning effect in cost specification of novel technologies.

2.2. Learning by doing (LBD)

Novel technologies are often expensive at the point of their market introduction but eventually become cheaper due to technological learning (Weiss, Junginger, Patel, & Blok, 2010). The technological learning—or, alternatively, learning effect—is a concept which permits the evaluation of the decrease in unit production costs when the cumulative production increases. It assumes that a technology's performance improves as experience with the technology accumulates. More specifically, for each doubling of cumulative production, the unit production costs decrease by a certain value known as the learning rate (LR). The literature identifies several major drivers of technological learning: learning-by-doing, learning-by-researching, learning-by-using, learning-by interacting and economies of scale firms learn from their production experience and accumulate an intangible organizational capital stock, which raises their future productivity. For literature review on the technological learning in energy–environment–economy modelling see (Kahouli-Brahmi, 2008).

LR notion is especially relevant in the context of novel process of natural resource utilization as in the discussed case of macroalgae. The process has not fully entered commercial production, but laboratory-based conversion technology is about to be scaled-up to an industrial-scale facilities of fermentation-derived products. The transition from small to big scale macroalgae cultivation is also expected to reduce costs as producers learn the environment, and detect optimal conditions for maximum yield.

Following (Kahouli-Brahmi, 2008), the basic representation of LR evaluation starts by assuming the cost per unit of production C as a function of quantity produced Q so that:

$$(1)\quad C(Q) = JQ^{-\mu}$$

Where J is the cost of the first unit produced, Q is the cumulative production and μ is the elasticity of learning by doing, which defines the effectiveness with which the learning process takes place.

Allowing Q_1 to be the cumulative production at time t=1, and allowing Ci to be the production cost at time i. A doubling of cumulative production costs implies that $Q_2 = 2Q_1$. LR is calculated so that:

(2) $LR = \frac{C_1 - C_2}{C_1} = 1 - \frac{C_2}{C_1} = 1 - \frac{J(2Q_1)^{-\mu}}{J(Q_1)^{-\mu}} = 1 - 2^{-\mu}$

Chen et al., (2017) review empirical studies on LRs in biofuels industry. They show an evaluated cost reduction in the range of 13%-35% as the cumulative production of biofuels doubles. Chen et al., (2017), like many other studies that incorporate learning effect in the cost function, follows by presenting a single stage dynamic programming framework for investigating time-dependent and adaptive decision-making processes to develop advanced fuel technologies.

In summary, the study on bioeconomy supply chain optimization has increased rapidly in recent years, covering various aspects of uncertainty and profitability. However, to the best of our knowledge, none of the existing work provided the methodological approach to two- stage production: from aquaculture of feedstock to biorefinery with multiple outputs. Moreover, the non-linearity of costs and the learning effect have not been explicitly addressed before.

3. The model

Here, we formulate the non-linear optimal control model. The model is constructed to represent a feedstock cultivation in the first stage of production, which is the input for biorefinery that processes the feedstock into of outputs *a* and *b*. At each stage of production and for each output, we assume non-linear cost functions with LBD.

Denote the cumulative production of feedstock, by X_{cum}, then x is the production of feedstock (macroalgae or other) at this particular moment, so that the state equation is:

(3) $x(t) = \frac{dX_{cum}}{dt}$

Then, denote by

(4) $X_{a,cum} = \int_0^t x(s)a(s)ds,$

Hence, $x(t)a(t) = x_a$, where $X_{a,cum}$ is the cumulative production of proteins, a is the share of feedstock used for production of proteins and x_a is the production of proteins at this particular moment.

Similarly, $X_{b,cum} = \int_0^t x(s)b(s)ds,$

Hence, $x(t)b(t) = x_b$, where $X_{b,cum}$ is the cumulative production of sugars, b is the share of feedstock used for production of sugars and x_b is the production of sugars at this particular moment.

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For simplicity, we assume that $X_{cum} = X_{a,cum} + X_{b,cum}$ and $x = x_a + x_b$ meaning no waste or residuals in the production process. It implies that X_{cum}, $X_{a,cum}$, and $X_{b,cum}$ are state variables and x, x_a, x_b are control variables.

Next, following (Kahouli-Brahmi, 2008) we assume non-linear production costs of proteins (Ca), sugars (Cb) and feedstock (C) that decrease with learning by doing:

$$(5)\quad C_a = \frac{Ax_a^{\phi}}{{X_{a,cum}}^{\psi}};\ C_b = \frac{Bx_b^{\xi}}{{X_{b,cum}}^{\zeta}};C = J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu}}$$

Where $\mu, \zeta, \psi < 1$ are the elasticities of LBD that define the effectiveness with which the learning process takes place in the processing of seaweed to proteins and sugars, and seaweed farming, respectively. The parameters $\phi > 1$, $\xi > 1$ indicate the marginal cost growth rate. The parameters *A, B* and *J* are costs of the first unit produced that may be calculated using one given point of the curve, usually the starting point (Kahouli-Brahmi, 2008), as for example:

$$(6)\quad J = \frac{C_0}{X_{cum0}{}^{-\mu}}$$

Now, denote by $P_a(t)$ and $P_b(t)$ the prices of outputs a and b respectively. Let the discount factor be r, then e^{-rt} is the continuous time discounting factor. Then, in the dynamic notion, the firm maximizes the following profit function:

$$(7)\ \max_{x_a, x_b} \pi = \int_T^{\infty}\left(P_a\, x_a + P_b\, x_b - A\frac{x_a^{\phi}}{{X_{a,cum}}^{\psi}} - B\frac{x_b^{\xi}}{{X_{b,cum}}^{\zeta}} - J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu}}\right)e^{-rt}dt$$

Next, define H as:

$$(8)\quad H = \left(P_a\, x_a + P_b\, x_b - A\frac{x_a^{\phi}}{{X_{a,cum}}^{\psi}} - B\frac{x_b^{\xi}}{{X_{b,cum}}^{\zeta}} - J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu}}\right)e^{-rt}$$

and apply the *Hamiltonian* equation as a first order condition for the optimization problem:

$$(9)\quad \frac{\partial H}{\partial X_{a,cum}} = \left[\psi A\frac{{x^{\phi}}_a}{{X_{a,cum}}^{\psi+1}} + \mu J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}}\right]e^{-rt};$$

$$(10)\ \frac{\partial H}{\partial X_{b,cum}} = \left[\zeta B\frac{{x^{\xi}}_b}{{X_{b,cum}}_b^{\zeta+1}} + \mu J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}}\right]e^{-rt};$$

$$(11)\ \frac{\partial H}{\partial x_a} = [P_a - \phi A\frac{x_a^{\phi-1}}{{X_{a,cum}}^{\psi+1}} - \frac{J}{(X_{a,cum}+X_{b,cum})^{\mu}}]\ e^{-rt};$$

$$(12)\ \frac{\partial H}{\partial x_b} = [P_b - \xi B\frac{x_b^{\xi-1}}{{X_{b,cum}}^{\zeta+1}} - \frac{J}{(X_{a,cum}+X_{b,cum})^{\mu}}]\ e^{-rt};$$

(13) $\frac{d}{dt}\left[\frac{\partial H}{\partial x_a}\right] = -re^{-rt}\ \frac{\partial H}{\partial x_a} + e^{-rt}\left[\dot{P}_a + \mu J \frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}} - \phi A\ \frac{(\phi-1)\,x_a^{\phi-2}\dot{x}_a X_{a,cum} - \psi\, x_a^{\phi}}{X_{a,cum}{}^{\psi+1}}\right];$

(14) $\frac{d}{dt}\left[\frac{\partial H}{\partial x_b}\right] = -re^{-rt}\ \frac{\partial H}{\partial x_b} + e^{-rt}\left[\dot{P}_b + \mu J \frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}} - \xi B\ \frac{(\xi-1)\,x_b^{\xi-2}\dot{x}_b X_{b,cum} - \zeta\, x_b^{\xi}}{X_{b,cum}{}^{\zeta+1}}\right].$

Where $\dot{x}_a, \dot{x}_b$ are growth rates of output a and b respectively, and $\dot{P}_a, \dot{P}_b$ are growth rates of prices over time. To find the solution we need to solve the following system of equations:

$$(15)\begin{cases}\frac{\partial H}{\partial X_{a,cum}} - \frac{\partial}{\partial t}\left[\frac{\partial H}{\partial x_a}\right] = 0\\ \frac{\partial H}{\partial X_{b,cum}} - \frac{\partial}{\partial t}\left[\frac{\partial H}{\partial x_b}\right] = 0\end{cases}$$

Then we obtain the following first order conditions (FOCs):

$$(16)\quad\begin{cases}\psi A \frac{x_a^{\phi}}{X_{a,cum}{}^{\psi+1}} + \phi A \frac{(\phi-1)x_a^{\phi-2}\dot{x}_a X_{a,cum} - \psi x_a^{\phi}}{X_{a,cum}{}^{\psi+1}} - r\phi A \frac{x_a^{\phi-1}}{X_{a,cum}{}^{\psi}} - \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}} - \dot{P}_a + rP_a = 0\\ \zeta B \frac{x_b^{\xi}}{X_{b,cum}{}^{\zeta+1}} + \xi B \frac{(\xi-1)x_b^{\xi-2}\dot{x}_b X_{b,cum} - \zeta x_b^{\xi}}{X_{b,cum}{}^{\zeta+1}} - r\xi B \frac{x_b^{\xi-1}}{X_{b,cum}{}^{\zeta}} - \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}} - \dot{P}_b + rP_b = 0\end{cases}$$

Proposition 1. The solution to *FOCs* is a global maximum of the firm problem.

Proof. Let us check that strict globalized version of Legendre condition is satisfied, since the second derivative $\nabla_{xx} H$:

$$(17)\ \nabla_{xx} H = \begin{bmatrix} -A\phi(\phi-1)\frac{x_a^{\phi-2}}{X_{a,cum}{}^{\psi}}\ e^{-rt} & 0 \\ 0 & -B\xi(\xi-1)\frac{x_b^{\xi-2}}{X_{b,cum}{}^{\zeta}}\ e^{-rt}\end{bmatrix}$$

is negative definite whenever $\xi, \phi > 1$. Therefore, we can imply the strict Weierstrass condition and guarantee that the obtained solution is a strong local maximum. Note as well, that since $\pi(x_a, x_b)$ is a concave function, then the second variation would be negative, therefore, the local maximum is also a global one.

Next propositions describe the comparative statics of the profit function.

Proposition 2. The profit is increasing in prices P_a, P_b and the elasticities of learning by-doing ψ, ζ, μ.

Proposition 3. The profit is decreasing in first-unit costs A, B, J, and marginal cost growth of output φ and ξ.

Proof. Propositions 2 and 3 can be proven by taking the derivatives of profit function with respect to the corresponding parameters. Note that none of the parameters depends on time. Therefore, taking the derivative of the integral functional is the same as taking the derivative of the functional under the integral sign.

Proposition 4. The profitability of producing output *a* increases the more output *b* is produced, and the opposite.

Proof: From *Equations 11* and *12*, it is evident that the more feedstock is produced in the first stage (macro algae), the faster is learning at the first stage of production, and the unit production costs decrease, no matter whether the feedstock was mainly processed into output *a* or *b*. The economic meaning is that co-production has a positive external effect. The more profitable output contributes to the increase in productivity in the first stage of production that serves as an input also to the less profitable output of Stage 2 (processing in bio-refinery). The product of Stage 1 accumulates faster, resulting cheaper unit costs to the benefit of all co-produced outputs.

Next, assuming that (at least some) of the parameters are random variables, we can concentrate on "probability" of increase/decrease in output. That is, the sign of the change in the probability measure changes in one of the observed parameters. Moreover, this type of inference can be drawn using the derivatives of the growth rate of output ($\dot{x}_a$ and $\dot{x}_b$). Since, if the derivative is positive, the higher the probability that the growth rate of output ($\dot{x}_a$ and $\dot{x}_b$) is positive. Therefore, the probability of increase in output level (x_a and x_b) to be increasing functions are higher. Note, that this relates to the future output rather than to the present one.

Proposition 5. The output growth rate increases as long as its price growth faster than the interest rate times price level.

Proof. Derive $\dot{x}_a$ or $\dot{x}_b$ from *FOC* (Equation 16):

$$(18)\ \dot{x}_a = \frac{{X_{a,cum}}^{\psi}}{A\phi(\phi-1)x_a^{\phi-2}} P_a\left(\frac{\dot{P}_a}{P_a} - r\right) and\ \dot{x}_b = \frac{{X_{b,cum}}^{\zeta}}{B\xi(\xi-1)x_{ab}^{\xi-2}} P_b\left(\frac{\dot{P}_b}{P_b} - r\right)$$

This result is particularly interesting. The dynamic nature of the model clarifies the intuition that if the price growth is higher than the discount rate, then increasing production is profitable. Otherwise, the investor would choose the alternative of keeping money in the bank.

Proposition 6. The probability of output growth is non-decreasing in output price growth, and non-increasing in output price level.

Proof: The derivatives of output growth rate with respect to the output price and its growth ratio are (we present derivatives only for output *a*, since for *b* they would look symmetric):

$$(19)\quad \frac{\partial \dot{x}_a}{\partial \dot{P}_a} = \frac{{X_{a,cum}}^{\psi}}{A\phi(\phi-1)x_a^{\phi-2}} \geq 0$$

Keeping in mind that the numerator in *Equation 19* represents learning and the denominator represents costs of the second stage of production, the result indicates that if the learning is faster than cost increase, then the output growth faster than prices.

$$(20)\, \frac{\partial \dot{x}_a}{\partial P_a} = -r\,\frac{{X_{a,cum}}^{\psi}}{A\phi(\phi-1)x_a^{\phi-2}} \leq 0$$

The insight of *Equation 20* is that higher interest rate favors present production over the future as more production today can generate more resources to be saved in the bank.

In the following sections 4 and 5, we demonstrate with simulations the feasibility and potential of the proposed optimal control supply chain design model.

4. Artificial Case-Study Setup

The artificial two-stage production was assumed in order to validate the accuracy of the model. The production process starts with cultivation of Kappaphycus, red macroalgae (first stage of production) that is utilized as the feedstock to the bio-refinery (second stage); the two outputs of the bio-refinery are industrial protein and Carrageenan. The actual data on model parameters was collected to provide insights about true profitability of macroalgae utilization to these chemicals. Table 1 presents for each model-parameter: its description, average value and range (if available), and the source (self-calculated and/or literature based).

Table 1: Model parameters, value, range and source

arameter	Description	Average Value	Range	Notes
	First unit cost of output *a* (protein)	4200 $/ton 2016	N. A.	Self-calculated from the price
	First unit cost of output *b* *(carrageenan)*	4500 $/ton 2014	4000-6500 $/ton 2010	(Brown, 2015)

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	First unit cost of feedstock (seaweed-Kappaphycus)	1 600 $/ton 2016	600-7000 $/ton 2010	Calculated based on FAO, 2013
ϕ	Marginal cost growth of *a*	5 %	0-20%	Assumed
ξ	Marginal cost growth of *b*	5 %	0-45%	Assumed
a	Price of output *a* (protein)	5 000 $/ton	1000-15000 $/ton 2016	Price calculated from value and quantity world *2016 Source:* UN COMTRADE; commodity 210610 protein; concentrates and textured protein substances
$\dot{P}_a$	Annual growth of Price output *a* (protein)	7 %	-43% to 92% in 1991-2016 s. d.	Price calculated from value and quantity Philippines and USA export 1991-2016 *Source:* UN COMTRADE; commodity 210610 protein; concentrates and textured protein substances
b	Price of output *b* (*carrageenan*)	5 500 $/ton	3000-6000 $/ton 2016	https://www.alibaba.com/trade/search?fsb=y&IndexArea=product_en&CatId=&SearchText=carrageenan
$\dot{P}_b$	Annual growth of Price output *b* (*carrageenan*)	4 %	-11% to 53% in 1991-2016 S. D. 16%	Price calculated from value and quantity Philippines export *Source:* UN COMTRADE; commodity HS130239 (mucilages and thickeners nes).
ψ	elasticity of learning by-doing (effectiveness with which the learning process takes place in the processing of	0.19	0.10 - 0.36	(Weiss, Junginger, Patel, & Blok, 2010)

	seaweed to proteins – soybean)			
ζ	elasticity of learning by-doing (effectiveness with which the learning process takes place in the processing of seaweed to sugars - *carrageenan*	0.35	0.29-0.41	(Chen, Zhang, Fan, Hu, & Zhao, 2017)
	elasticity of learning by-doing in seaweed farming – Kappaphycus	0.42	0.15-0.69	(Weiss, Junginger, Patel, & Blok, 2010)
	Annual discount rate	4%	0-10%	Assumed

5. Simulations

To facilitate the intuition behind the model, we present the results of the simulations of the asymmetric model with three basic scenarios considering the parameters' values presented in Table 1: pessimistic, average and optimistic. In addition, for each scenario, we perform sensitivity analysis to investigate the impact of key parameters on the robustness of the results. In general, we keep the growth rate of marginal costs of outputs *a* and *b* to be constant over all the scenarios and equal to $\phi = 1.05$ and $\xi = 1.1$ respectively. Later on, we show the effect of increase in marginal costs' growth rate. Another parameter kept constant over the simulations is the discount rate: $r = 4\%$. Price growth rates are also kept constant to the estimated average level inferred from 7% price growth rate for protein (output *a*) and 4% for *Carrageenan* (output *b*).

5.1. Average Scenario

In this scenario, we set all the parameters to the average values as of Table 1:

$$P_a = 5000; P_b = 5500; A = 4200; B = 4500; J = 1600; \psi = .19; \zeta = .35; \mu = .42$$

For the average values of first unit costs for each output at each stage (*A, B, J*), corresponding learning rates (ψ, ζ and μ), and output prices (P_a and P_b), we observe positive production of both outputs (Figure 1), with NPV of about $2.2 * 10^8$ \$ in 2016 values.

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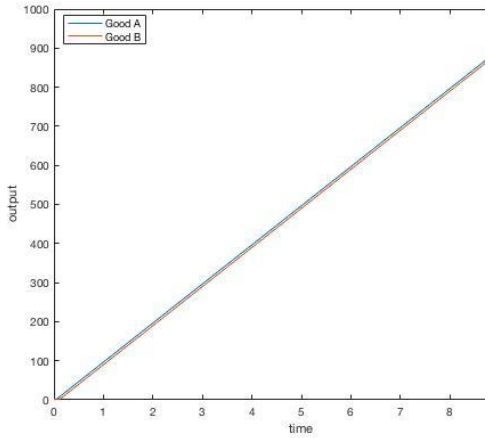

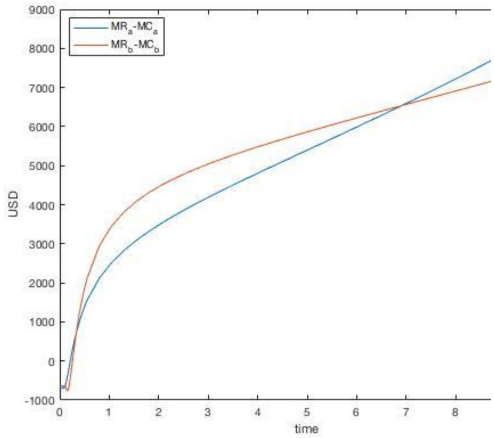

Figure 1. Production

Figure 2. Difference between Marginal Revenue (MR) and Marginal Costs (MC) for every good

Moreover, Figure 2 shows that for both goods, the marginal profit (marginal revenue minus marginal costs), even though negative at the beginning, stays positive after some point. The profitability of producing output *b* (*Carrageenan*) is higher and growths relatively faster in the beginning. This is due to the higher initial price and LBD rate. However, over time, the accumulation of feedstock production (and therefore knowledge and experience) reduces the costs of first stage to output *a* (protein) as well. At the same time, the price growth for output *a* is higher, leading eventually to higher profitability of protein over *Carrageenan*.

The additional reasoning for switch in profitability between output *a* and *b* can be illustrated by LBD trajectories (Figure 3). For this purpose, we consider only the component of costs that corresponds to the learning by doing $\frac{A}{x_a^{\psi}}$ and $\frac{B}{x_b^{\zeta}}$:

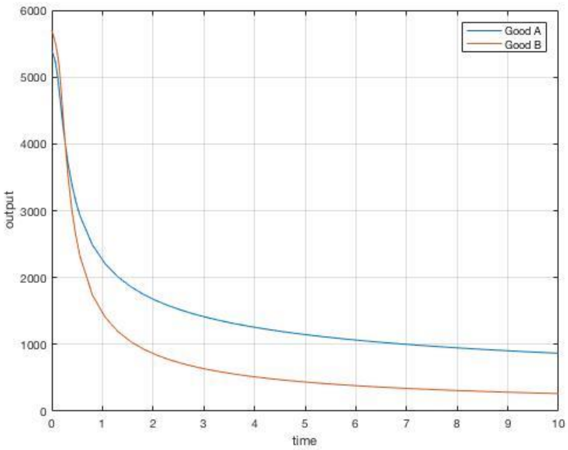

Figure 3. Learning Cost Components

We can see that in the beginning, LR for good B is higher – its processing cost declines steeper. At some point, the curves become parallel implying that the change in costs due to LBD is similar for both goods.

Zooming in Figure 1, for a closer look at the production in the very beginning

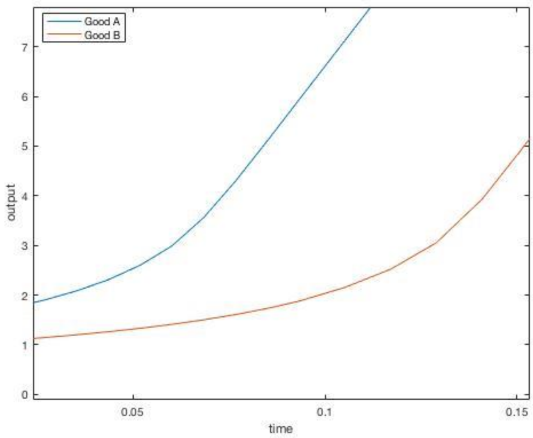

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Figure 4), becomes evident that more of good a is produced, and, its production grows faster than one of good b.

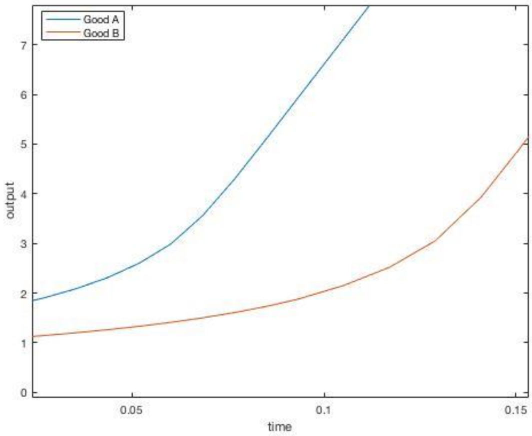


Figure 4. Output at the early periods

Recall that good a's production is cheaper in the beginning (the first unit cost is lower than that of output b: $A<B$). And, its initial price is lower ($P_a<P_b$). However, it has a higher price growth rate ($\dot{P_a} > \dot{P_b}$). Therefore, given that firm has a perfect foresight it would invest more in output a.

5.2. Average Scenario: Sensitivity Analysis

5.2.1. All parameters at average level with one at the pessimistic level

If we just switch the first unit cost at the cultivation stage, J, to the highest (pessimistic) level of 7000, we immediately obtain inefficiency and zero production schedule. Note that if we keep J at the average level and change B to the pessimistic level we would not see such a radical shift. There will be positive profit with positive production of both outputs of the second stage. Changing LBD coefficients to the pessimistic level would not alter production schedules qualitatively as well.

If we set the initial prices to the lowest (pessimistic) level, then we still obtain positive output schedule. However, there is an important change in the profit trajectory. For the average scenario it is immediately profitable to produce both goods. While with the pessimistic prices, the profit in the very beginning is negative. That is, the learning effect stimulates the entrepreneur to sacrifice some of the current outcome for the sake of the later profits.

5.2.2. The tradeoff between initial costs and learning rates

Setting $J = 4000$, then at the average learning rates the optimal production plan is zero, while if we change the learning rates to the optimistic ones, we observe the positive production plans. Moreover, in this case it is immediately profitable to produce both goods (Figure 5, Figure 6). Hence, at the less radical levels of the first-unit costs we can see that there is a substitution between the learning rates and first-unit costs.

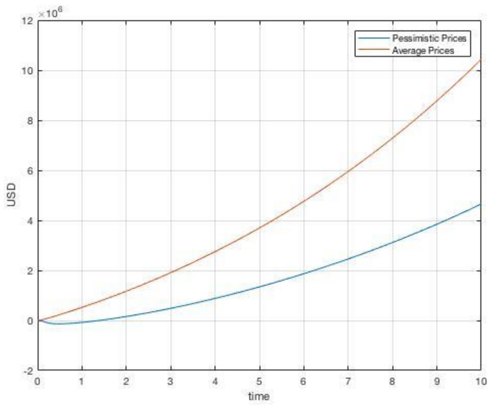


Figure 5. Momentum Profit for Different Price Configurations

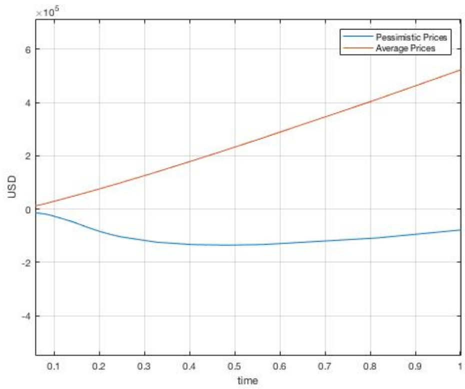


Figure 6. Zoomed Momentum Profit for Different Price Configurations

Note, that FAO (2013) report of actual costs of Kappaphycus cultivation in the developing countries indicates that most of the investment and capital costs (*i. e.* first unit costs) of seaweed are within the 600- 1600 $/ton. The 7000 $/ton is the far-end outlier. Therefore, we can conclude that LBD can reverse non- profitable production into the profitable even for relatively high costs of cultivation.

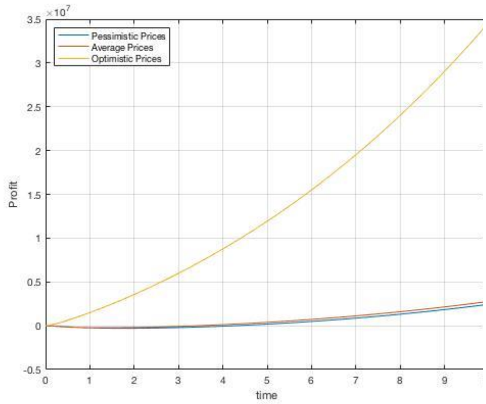
5.3. Pessimistic scenario and the sensitivity analysis

In the pessimistic scenario, we set the revenue related parameters and the LBD elasticities at the lowest rates, while the cost related parameters are set at the highest values:

$$P_a = 1000; P_b = 3000; A = 4200; B = 6500; J = 7000; \psi = .10; \zeta = .29; \mu = .15$$

We do not observe any production with all parameters set at the pessimistic value. However, if we set first-stage first-unit cost at the lowest (optimistic) level $J = 600$, we obtain positive production of both outputs. Moreover, the profit in the beginning is negative, indicating that the production operates solely for learning, and afterwards become positive. Therefore, it is a profitable decision to start investing into learning and producing both goods, even if the outputs' prices are low.

Next, we consider variation in prices (P_a, P_b), while keeping J at the lowest level and other parameters at the pessimistic levels (Figure 7). We see that under pessimistic and average prices there is an active learning stage, while switching prices to the optimistic level makes it profitable to produce both goods from the very beginning (Figure 8).



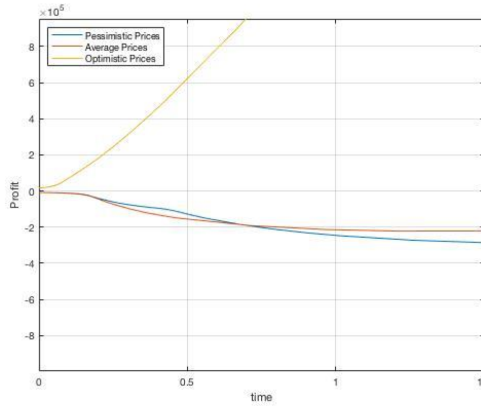


Figure 7. Profit Trajectory

Figure 8. Zoomed Profit Trajectories

Next, consider low J and pessimistic level of prices. Figure 9 shows that for output *b*, at some point in time, marginal costs (MC) become lower than marginal revenue (MR), due to both: price growth and LBD effect, allowing for accumulation of positive profit.

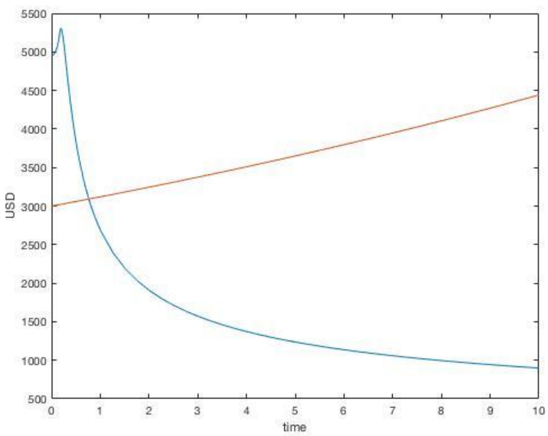


Figure 9. Marginal Costs (MC) and Marginal Revenue (MR) from producing B

Setting up only one of the first unit costs to the optimistic level does not change the production decision if J is at the pessimistic level. Moreover, switching both learning by doing parameters to the maximum would not guarantee positive production schedule.

5.4. Optimistic Scenario

In the optimistic scenario, we set the revenue related parameters and the LBD elasticities at the highest rates, while the cost related parameters are set at the lowest values:

$P_a = 15000; P_b = 6000; A = 4200; B = 4000; J = 600; \psi = .36; \zeta = .41; \mu = .69$

If we setup all the coefficients to their optimistic values, then we clearly obtain positive production schedule with immediate profits. Moreover, if we set J to the pessimistic value (keeping all the rest constant) we still get positive production. Moreover, due to the high enough initial prices the profits are immediate. In addition, keeping J at the pessimistic level and altering other parameters, we can switch from immediate profitability to profitability at some point in the future, though still having the positive output schedule.

5.5. Changing elasticity of marginal costs

Further, we investigate the impact of higher growth rate of marginal costs of the second stage of production ($\varphi = 1.2$ and $\xi = 1.45$), while preserving rest of the parameters at the average scenario level. Two important outcomes are revealed (Figure 10 and Figure 11):

First, the production of output *b* (with higher cost growth and lower price growth rates) is delayed, creating a larger gap between the production paths of outputs *a* and *b*.

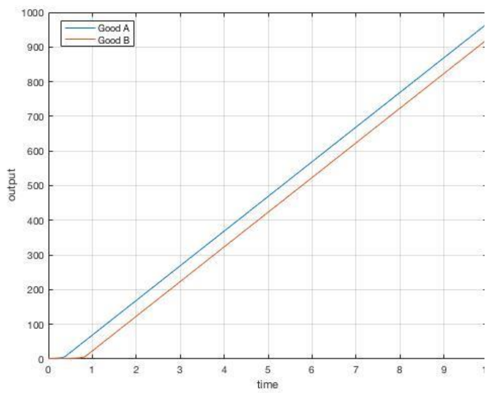


Figure 10. Output under higher elasticity of marginal costs

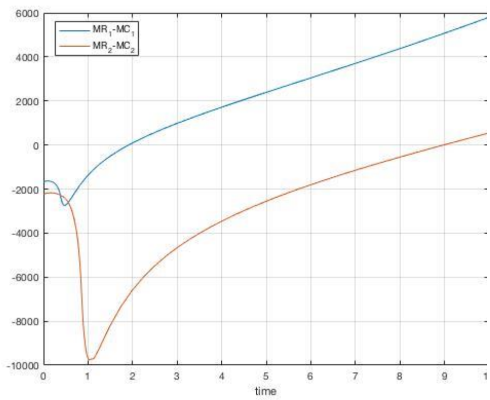


Figure 11. Momentum Marginal Profits

In this case, the difference between the marginal costs is substantial, therefore, especially in the early stages mainly good A is produced. Though, at the point when it becomes cheap enough to produce first-stage output, we observe the fast growth in production of both goods.

Second, the marginal profit of output *a* is higher than one from *b* (Figure 11) during the lifetime of the project. In addition, there is a longer active learning period for good B due to delay in its production.

Finally, Figure 12 presents the impact of higher elasticities of marginal costs on the profit.

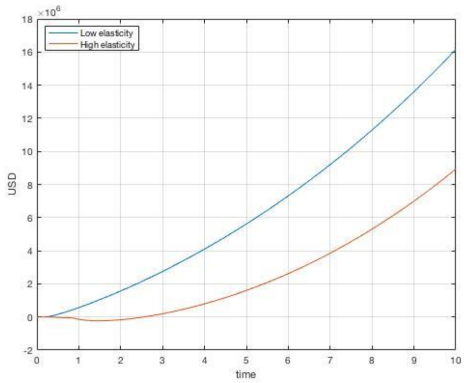


Figure 12. Profit trajectories at different marginal costs

Evidently, higher cost growth rates shift the profit curve down. Moreover, we observe a qualitative change in the profit trajectory. As the elasticities increase, there is a longer active learning stage, when the entrepreneur absorbs losses for the sake of future profits.

6. Discussion

This study investigates the economic opportunities and challenges of macroalgae utilization. The focus on macroalgae is driven by the fact that being cultivated off-shore, they do not compete for scarce land and potable water. In addition, recent developments in bio-refinery show the potential to produce not only food and coloring, but also sugars for biofuels, proteins, and high value chemicals.

The contributions of our paper to the literature are manifold. First, we propose a two-stage dynamic optimal control model for the design and management of a macroalgae-based supply chain. The model is applied to micro-level decision making, taking into account key supply chain components, e.g. cultivation and refining. To the best of the authors' knowledge, this study presents a unique modeling approach that explicitly takes into account non-linear stage-specific production costs, and introduces the learning effect. The rate of macroalgae growth and the conversion factors – two key parameters in productivity- show a wide range of values. Therefore, learning with research and experience have a major effect on cost effectiveness of the technology.

Second, the novelty of our work is in proposing the model with multi-output profile of the second stage and deriving the conditions for profitable production bundle.

Finally, a series of simulations with real-data based parameters is presented to validate the effectiveness of the model and the theoretical insights. The analysis allows answering the key policy questions of supporting novel technologies that involve multi-stage co-production process.

The importance of the research is in emphasizing the three key pillars in the supply chain based on the novel technology: the initial (fixed) costs, output prices and learning. The theoretical and simulation results highlight the need of reducing the fixed costs of utilization as well as increasing the marketing effort that rises the price of the final product.

The results reveal that cultivation costs have higher impact on profitability than processing in the biorefinery even if the processing allows for several outputs. Thus, the R&D effort should primary address the cultivation stage. Gaining knowledge and experience in best off-shore cultivation practices is the key to boosting the mass utilization of the renewable resource – macroalgae. Moreover, the simulations indicate that production costs at the developed countries can be sensitive to the learning effort. R&D is required to reduce the fixed cost of macroalgae cultivation. Here, the fundamental practical question is what will cause the faster decline in the fixed cost: further basic research or more experiments in the field?

The next central element is the determinants of the price of the final product. Discovering additional uses of macroalgae-based products can generate higher value. For instance, developing novel uses to proteins and sugars and other unique chemicals extracted from macroalgae at the biorefinery, can boost the viability of the utilization. To generalize, rather than competing with existing goods, the scientific challenge can be the investigation of the potential to utilize macroalgae for unique foods, high value chemicals and fuels. In addition, a marketing campaign to increase the perceived benefit of the final product can make a major difference in the profitability of the production.

This work can be extended in several directions. In the future research, the dynamic setting of Option Value modeling is recommended. Allowing for volatile prices dynamics, will enforce investigating the tradeoff between researching effort and price variability. For example, taking into account price volatility, the entrepreneur might introduce the product in the period when the price is high. Then, the question is, what learning effort will allow the entrepreneur to operate even if the price declines later on. More investigation on the impact of output price variability on technology adoption decisions is essential.

Next, as the simulation results show that under reasonable conditions, macroalgae utilization can be profitable for protein and sugar production, the additional aspect for future research should be the introduction of carbon saving. Negative and positive externalities of macroalgae-based biofuel production should be investigated in order to verify the potential of macroalgae utilization for climate change mitigation effort. Further analysis on macroalgae external costs and benefits is required for an accurate policy intervention**.** The analysis on the technological prospects of macroalgae biorefinery should evaluate the social net benefit too.

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Changes to Original Research Plan

No major changes were made

Training of Students and Postdocs

Name	
Liran Voldman	M.Sc. Student
Alexander Gladkov	M.Sc. Student
Dr. Meghanat Prabu	Postdoc
Arthur Robin	PhD student
Benjamin Gordon	PhD student
Molly Van Dop	PhD student